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Autonomous Viewpoint Selection of Robots Based on Aesthetic Composition Evaluation of a Photo

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***Abstract*—In the field of painting and photography, composition rules are widely used under various circumstances in order to arouse humans' aesthetic evaluation. In this paper, we propose a method to evaluate the aesthetic values of a scene according to some certain composition rules, such as Rule of Third, Diagonal Composition and Triangle Composition. We propose an evaluation function with three factors for each kind of compositions, which is reasonable to describe properties of compositions as the result showed in our questionnaire. We develop an observation position searching method by estimating relationships between targets from different viewpoints of the monitoring robot. Then a score will be obtained for each viewpoint using our evaluation function. By these scores, the best observation position can be determined within a reachable field. With path planning and moving control, the monitoring robot arrives at the best observation position. We suppose our research can provide any hint about common understanding between human beings and robots.**

I. INTRODUCTION

Recently, with the development of image processing technologies, researchers have attempted to enhance aesthetic appreciation of images by transforming humans' evaluation into computable parameters, using some methods to adjust arrangements of targets following some aesthetic composition rules. Several achievements have been made. For example, Vidya Setlur et al.[5] presents a retargeting algorithm in which relationships of targets remain recognizable and pleasing while the size of images changes. Liu et al.[6] and Zhang et al.[7] also propose similar algorithms to adjust sizes and positions of foreground objects based on Rule of Third by cropping and trimming original images. However, these methods sometimes cause uneasy or uncomfortable feelings of humans because targets are forced to change their semantic characteristics in a photo. Seeking a position where aesthetic compositions of targets can be found is considered to be a more effective way than rectifying arrangements of targets after photos have been shot.

In the field of robotics, researchers try to use monitoring robots for observation point searching. Z.Byers et al.[8] develop an autonomous photographer robot to search for a pleasing composition according to Rule of Third in some events or ceremonies. Although their system can sometimes obtain a satisfying composition, the success ratio is only 29 percent because the viewpoint-searching process is quite hazardous and whether a good composition can be found or not remains unknown until the photographer robot stands at the observation position.

Composition rules, which are introduced in many professional textbooks about painting and photography[3][4], are often used to evaluate aesthetic values of a scene. For example, the famous Rule of Third, Diagonal Composition, Triangle Composition and so on. In our research, we propose an evaluation function with three factors for each kind of compositions mentioned above. We employ an object segmentation method by the depth information[9] for object detection. In order to raise the success ratio of our system, we set alternate observation positions around targets and estimate aesthetic values using our composition function for each position in advance without the robot reaching it. We hope our research can provide any hint about the common comprehension between humans and robots.

This paper below consists of six sections. Section II introduces compositions employed in our research and the formation of evaluation function for each kind of composition. Section III shows the consistency between our function and human evaluation according to the result of a questionnaire survey. Section IV is about the estimating process of the best observation position. In Section V we introduce the architecture of our system generally while in Section VI, we verify validity of our algorithm through experiments. At last comes the conclusion and future work about our research.

II. COMPOSITION EVALUATION FUNCTIONS

A. Aesthetic Compositions

In the field of visual art, compositions emphasize the arrangement of visual ingredients according to some rules of aesthetics, which play an essential roll in the creating process of artistic works. Although artistic creation is not rigidly adhere to a certain form, some heuristic composition rules are summarized from humans' daily life and now are accepted by almost all of human beings to arouse their pleasing emotions.

Different compositions are employed to express different subjects of photographers. Photos constructed in Rule of Third reflect a balanced collocation of targets, those in Diagonal Composition bring a dynamic expression even though targets in a photo keep still all the time, while photos in Triangle Composition show both stability and variety hidden behind the targets. As compositions pay attention to relationships and geometric structures of targets[7], we also pay attention to these factors and attempt to change

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(a) (b) (c)

Fig. 1: Typical Compositions of Photographs. (a) Rule of Third. (b) Diagonal Composition. (c) Triangle Composition.

these factors into computable values for aesthetic evaluation of ordinary images. Figure 1 shows examples of composition rules we use in this paper.

B. Subfuntions for Composition Evaluation

Balance, size and the fitting value to composition rules are three important factors which must be considered when people evaluate the aesthetic values of a photo based on some composition rules. In this paper, we will define three functions (we call them subfunctions in following sections) to evaluate each factor mentioned above and create a total function to evaluation the aesthetic values of a photo using them. We neglect the influence of background temporarily because in most situations the background of a scene does not change violently when we try different observation positions. For convenience, we divide these three subfunctions into two groups, naming common functions and fitting value functions. Common functions include visual balance subfunction and region size subfunction and their definition are the same in different compositions. Fitting value functions measure the precisions when we evaluate scenes based on one certain composition rule, by which we can tell one composition from another.

Mathematical formations of factors are based on the information of targets in photos, so we only consider pixel coordinates of targets when talking about composition evaluation functions. The following subsections will introduce these functions mentioned above for composition evaluation.

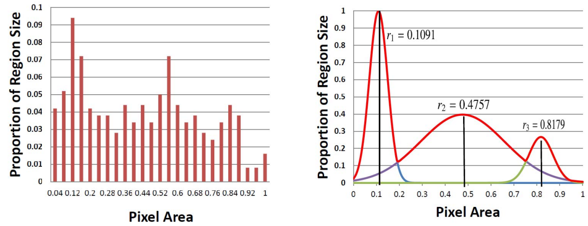
C. Common Functions

A pixel is the smallest addressable and controllable element of a digital picture represented on the screen. It is often represented as a dot or square in a two-dimension grid. Although positions of pixels can be localized in a Cartesian coordinate, it is not appropriate to measure the distance between two pixels using the traditional Euclidean Distance. In image processing procedure, we bring in a concept of Manhattan Distance d to describe the relative position relationship between two points $p_1(x_1, y_1)$, $p_2(x_2, y_2)$. If w,h are width and height of a photo in a pixel coordinate, a normalized Manhattan Distance is defined as follows:

$$d(p_1, p_2) = \frac{\mid x_1 - x_2 \mid}{w} + \frac{\mid y_1 - y_2 \mid}{h}. \quad (1)$$

a) *Visual Balance*

A balanced arrangement, which is different from geometric symmetry, refers that the center of salient regions is nearby the image center[8]. Since balance reflects humans' aspirations to peace and calm, we define a Visual Balance subfunction as a factor for composition evaluation.



(a) (b)

Fig. 2: Distribution of Region Size. (a) Size Analysis of [6]. (b) Approximate Result.

We utilize the normalized Manhattan distance d_{vb} between the center of targets group (G) and center of image frame (C) as a measurement for visual balance,

$$d_{vb} = d(G, C). \quad (2)$$

The definition of Visual Balance subfunction E_{vb} is as equation (3). Scores vary from 0 to 1 and a higher score means a better balance of vision.

$$E_{vb} = e^{-\frac{d_{vb}^2}{\sigma_1}}. \quad (3)$$

σ_1 is 0.05 from the result of our experiments.

b) *Region Size*

Region Size also has an outstanding influence on compositions. Liu et al.[6] made a survey on the size of salient regions in a picture for over 200 professional photographs and drew a histogram of the result. Although images were collected from various kind of fields, three dominant peaks were found which represent humans' customs and tastes when they are appreciating works of art with an aesthetic vision. Figure 2 (a) shows the result of Liu[6] et al.

We realize that people show an inclination to obtain a high evaluation when the proportions of region sizes in photos are near the value of 0.12, 0.56 and 0.82. We employ this conclusion for Visual Size evaluation. As Visual Size subfunction should be applied for all sizes of targets, we transform these discrete values into three continuous Gaussian curves due to the three dominant peaks. For each value in the horizontal axis, we choose the highest vertical value from the three Gaussians and link all of the highest values. At last we enlarge the largest vertical value to 1 because we need the Vision Size evaluation function E_{sz} to vary from 0 to 1. Figure 2 (b) shows the curve.

If $M(S_i)$ is the region area of S_i, n is the number of targets, r_j is the horizontal coordinates of curve peaks, the evaluation function E_{sz} can be defined as follows:

$$E_{sz} = \max_{j=1,2,3} e^{-\frac{\left(\sum_{i=1}^{n} M(S_i) - r_j\right)^2}{\omega_j}}. \quad (4)$$

Values of r_1, r_2, r_3 are separately 0.109, 0.476 and 0.818. w_1, w_2, w_3 are constants with values of 0.003, 0.067 and 0.006.

D. Fitting Value Functions

Every composition has some particular characteristics which make it distinct from others. In this paper, we employ three kind of compositions for example and construct a Fitting Value function to measure the precision for each kind of composition rules.

a) *Rule of Third*

If we divide all edges of a photo frame into three parts equally and draw a straight line between every two cut-points in an opposite position, we will get four crossing points P_j. They play a very important role to evaluate positions of targets in this kind of composition. Rule of Third is an application of the golden ratio[2] and high aesthetic evaluation will be obtained in places near a crossing point.

If we use $d(S_i) = \min_{j=1,2,3,4} d(C(S_i), P_j)$ to represent the minimal Manhattan distance between targets' center $C(S_i)$ and four crossing points P_j, feature evaluation function of Rule of Third E_{rt} can be defined as follows:

$$E_{rt} = \frac{\sum_{i=1}^{n} M(S_i) e^{-\frac{d_{S_i}^2}{\sigma_2}}}{\sum_{i=1}^{n} M(S_i)}. \tag{5}$$

σ_2 is 0.04. Scores of this parameter vary from 0 to 1.

b) *Diagonal Composition*

Diagonal Composition highly appraises arrangements that centers of all targets are in a line coinciding with diagonals of screen as Fig.1 (b). By calculating the absolute values of angles with a diagonal, which are smaller than $\pi/2$, we design a function E_{dr} for this kind of composition. Since there are two diagonals in one frame, two sets of angles α_{ij} , β_{ij} will form with different diagonals. Angles in the same set are formed with the same diagonal.

We compute E_{dr} with two sets of angles and choose the larger value for use,

$$E_{dr1} = \frac{2}{n(n-1)} \sum_{i=1}^{n} \sum_{j>i}^{n} e^{-\frac{4\alpha_{ij}^2}{\pi^2}}, \tag{6-1}$$

$$E_{dr2} = \frac{2}{n(n-1)} \sum_{i=1}^{n} \sum_{j>i}^{n} e^{-\frac{4\beta_{ij}^2}{\pi^2}}, \tag{6-2}$$

$$E_{dr} = max\{E_{dr1}, E_{dr2}\}. \tag{6-3}$$

c) *Triangle Composition*

Triangle Composition is also a common composition which has a wide usage in photography community. Some kind of particular triangles, for instance, isosceles triangles, regular triangles and right angled triangles, are acknowledged to have a mysterious beauty introduced in many works[9] with a mathematical explanation. However, Triangle Composition doesn't demand targets, which are usually treated as vertexes, to be placed in a position where they can shape a particular triangle. Triangles are in a more flexible form to professional photographers. We can merely find targets in a shape of particular triangles from any artistic works.

Considering this situation, we make use of the golden ratio and pixel areas of the hollow triangles formed by targets as a measurement of Triangle Composition. The application of the golden ratio in art can be traced back to the twentieth century, when Some artists and architects, including Salvador Dalł and Mondrian, have proportioned the targets of their works to approximate the golden ratio, believing this proportion to be aesthetically pleasing[11]. Since the golden ratio are now well-accepted as a famous aesthetic and natural law, we here borrow the concept of the golden ratio to construct this parameter. We first prescribe a sample triangle whose width compared with the longer side of a picture equals the golden ratio while height compared with the shorter side also equals the golden ratio. We compute the pixel areas of the sample triangle and formulate feature parameter of triangle composition E_{tr} as equation (7). S_0 is the pixel area of the hollow triangle formed by objects. S shows the pixel area of the whole frame. Φ represents the golden ratio. σ_3 equals 0.04.

$$E_{tr} = e^{-\left(\frac{S_0}{S\sigma_3} - \frac{\Phi^2}{2\sigma_3}\right)}. \tag{7}$$

TABLE I: Correlation Analysis of Parameters for Rule of Third

correlation	E_{rt}	E_{vb}	E_{sz}
E_{rt}	1	-0.28	0.47
E_{vb}	-0.28	1	-0.10
E_{sz}	0.47	-0.10	1

TABLE II: Correlation Analysis of Parameters for Diagonal Composition

correlation	E_{dr}	E_{vb}	E_{sz}
E_{dr}	1	-0.32	0.71
E_{vb}	-0.32	1	-0.10
E_{sz}	0.71	-0.10	1

TABLE III: Correlation Analysis of Parameters for Triangle Composition

correlation	E_{tr}	E_{vb}	E_{sz}
E_{tr}	1	0.43	0.00
E_{vb}	0.43	1	0.18
E_{sz}	0.00	0.18	1

E. Correlation of Subfunctions

In our system, we are aiming to construct a total evaluation function with three subfunctions for each kind of composition to evaluate aesthetic values of photographs. So inspecting these three subfunctions whether measure different properties of an image or not is a must. We prepare 50 photos for each composition and do a correlation analysis between each two of them to make sure whether they can be treated as independent factors. Imaging the situation when a professional photographer is shooting a scenery or a still life, these photos are with the same objects as targets in the same background to get rid of influences of other unknown factors.

Table I, II and III shows the result of our correlation analysis, suggesting that three subfunctions measure different properties of photos.

F. Evaluation Function of Composition

In this subsection, we will give a weight to the value of each subfunction in order to accomplish the evaluation functions for different compositions. We gathered 17 ordinary people ($m = 17$) for a questionnaire in which they should evaluate the aesthetic values of 50 sample photos ($M = 50$) according to the standards of Rule of Third, Diagonal Composition and Triangle Composition. They scored each picture with a round number from 1 to 5.

As humans' personal preferences vary from each other, we received different scores for the same sample photo. Suggesting that the score of Photo No.p from the qth tester is recorded as h_p^q, we can calculate the average score of each sample photo to represent humans' aesthetic evaluations towards it. The average score for Photo No.p ($\bar{h}_p$) is as follows:

$$\bar{h}_p = \frac{1}{m}\sum_{q=1}^{m} h_p^q. \tag{8}$$

The results of the evaluation functions should have a positive correlation with humans' subjective evaluation. In order to construct these evaluation functions, the consistency between subfunction values and humans' evaluation scores should be examined. Taking Rule of Third for example, we made a distribution map for subfunction values and humans' average evaluation scores. In Fig.3 (a), (b) and (c), the horizontal axis shows scores of humans ($\bar{h}_p$) while the vertical axis are values of E_{rt}, E_{vb} and E_{sz}. We confirmed a straight line by the Least Square Method and made use of the Root Mean Square Error(RMSE) to evaluate the dispersion of the three distributions based on the straight line. Expected values can be estimated from the line. If realistic values of E_{rt}, E_{vb} and E_{sz} for Photo No.p are recorded as E_{rt}^p, E_{vb}^p and E_{sz}^p, expected values are $\bar{E}_{rt}^p$, $\bar{E}_{vb}^p$ and $\bar{E}_{sz}^p$, RMSE can be calculated as follows:

$$RMSE(E_{rc}) = \sqrt{\frac{1}{M}\sum_{p=1}^{M}(E_{rt}^p - \bar{E}_{rt}^p)^2}, \tag{9-1}$$

$$RMSE(E_{vb}) = \sqrt{\frac{1}{M}\sum_{p=1}^{M}(E_{vb}^p - \bar{E}_{vb}^p)^2}, \tag{9-2}$$

$$RMSE(E_{sz}) = \sqrt{\frac{1}{M}\sum_{p=1}^{M}(E_{sz}^p - \bar{E}_{sz}^p)^2}. \tag{9-3}$$

We normalized reciprocals of the three RMSE as their weights in order to decrease the dispersion of function's distributions. Using the same method, evaluation functions E_{rc}, E_{dc} and E_{tc} became as follows:

$$E_{rc} = 0.35E_{rt} + 0.28E_{vb} + 0.37E_{sz}, \tag{10-1}$$

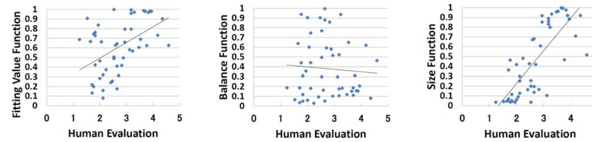
$$E_{dc} = 0.36E_{dr} + 0.28E_{vb} + 0.36E_{sz}, \tag{10-2}$$

$$E_{tc} = 0.47E_{tr} + 0.27E_{vb} + 0.26E_{sz}. \tag{10-3}$$

Where E_{rc}, E_{dc} and E_{tc} represents aesthetic evaluation score for Rule of Third, Diagonal Composition and Triangle Composition, which varies from 0 to 1.

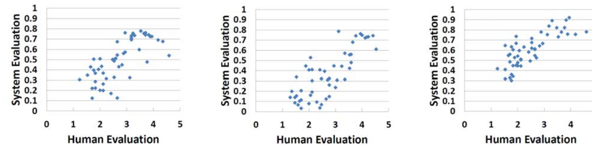
III. Consistency to Humans' Evaluation

Figure 4 shows the distribution of function values and humans' evaluation scores. The abscissas are evaluation scores of human and the ordinates are scores of our functions. In order to examine the consistency between system and humans' evaluation, we employ the correlation coefficient as a measurement.



(a) (b) (c)

Fig. 3: Distribution of Subfunction Values and Humans' Evaluation Scores. (a) Feature Parameter. (b) Balance Parameter. (c) Size Parameter.



(a) (b) (c)

Fig. 4: Distribution of Function Values and Humans' Evaluation Scores. (a) Rule of Third. (b) Diagonal Composition. (c) Triangle Composition.

When the value of the correlation coefficient is over 0.7, a strong correlation is admitted. After calculating the correlation coefficients for Figure 4 (a), (b) and (c), we got the results of 0.73, 0.8 and 0.79, showing a high consistency between our evaluation function and humans' subjective emotions.

IV. Selection of Observation Position

We develop a novel algorithm for robots to search for the best observation position[1]. By estimating the relationship of targets in different observation position based on coordinates and angles at present in the real world, we can get the result of each parameter before a robot reaches the position.

Figure 5 shows parameters used to calculate pixel information in different observation positions. Pixel coordinates (x_i', y_i') and area $M'(S_i)$ of Target i are estimated as follows:

$$x_i' = \frac{2}{W}\frac{\tan\theta_i}{\tan\varphi}, y_i' = \frac{2}{V}\frac{\tan\gamma_i}{\tan\varphi_2} \tag{11-1}$$

$$M'(S_i) = M(S_i)\left(\frac{d_i}{d}\right)^2. \tag{11-2}$$

Where W and V are pixel width and height of a picture's frame, d is distance between Target i and camera while d_i is distance between expected observation position and camera.

With x_i', y_i' and $M'(S_i)$, we can estimate the values of factors for different composition rules using equations (1) from (7). Then total evaluation functions can be calculated by equation (10) for all the alternate positions. That is to say, when a monitoring robot stands at one observation position, we can evaluate the aesthetic values of all other alternate positions. The best observation position is determined with the highest score according to our evaluation functions. Figure 6 is a viewpoint map from a vertical view. Different function scores are represented in different colors. Higher scores are in blue while lower scores are in red. S shows the position where the monitoring robot is at present, while G is the best observation position estimated.

V. Observation Position Selection System for Aesthetic Scenes

Figure 7 shows the system architecture. It consists of five modules: *Image Processing*, *Composition Evaluation*, *B.O.P*

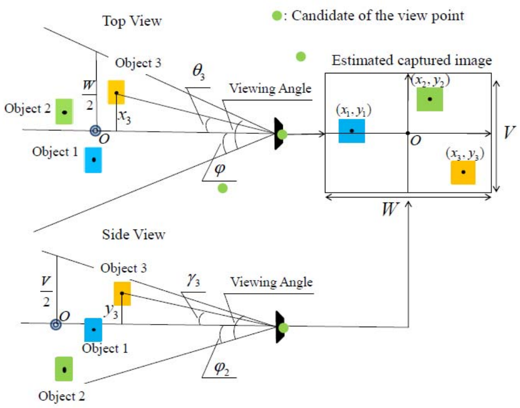


Fig. 5: Top View and Side View of Targets.

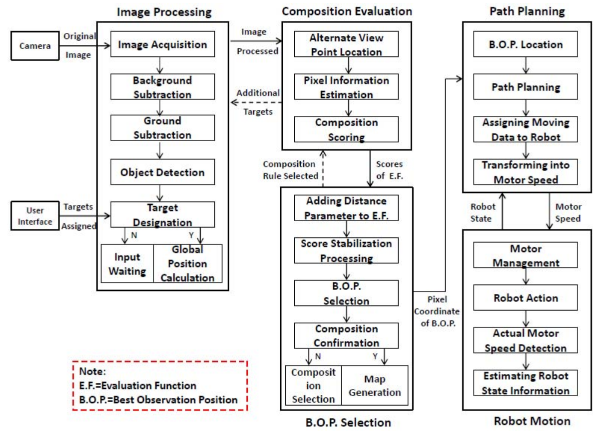


Fig. 7: Observation Position Selection System for Aesthetic Scenes.

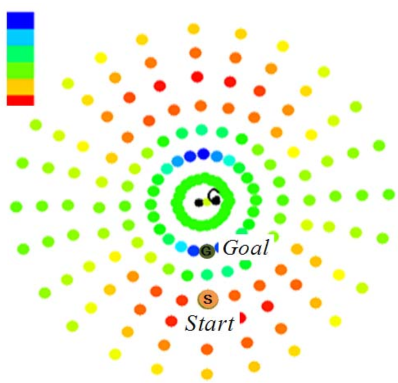


Fig. 6: Composition Map.

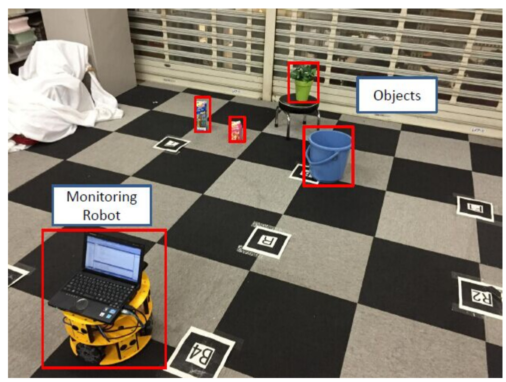


Fig. 8: Experimental Environment.

(the Best Observation Position) Selection, *Path Planning for monitoring robots* and *Robot Motion Control*. Each module is independent and has a communication with others.

Two kinds of input are necessary to our system and the absence of any input will lead to a failure. Primary input of the system is original images taken from a RGB-D camera. Also, an optional input is the designated targets, which is employed based on the user's preferences through a user interface.

In *Image Processing* module, original images are input to the system. Targets can be detected and the position information in both pixel and global coordinates can be calculated or estimated using the information from the RGB-D camera. After designated targets are input through the user interface, position information concerned with these targets is sent to the *Composition Evaluation* module.

In *Composition Evaluation* module, based on the information gathered from other modules, the system will set some alternate viewpoints and judge composition values for each observation point using composition evaluation functions we proposed. Composition scores and the position information in the global coordinate will be both considered in *B.O.P Selection* module.

The B.O.P will be confirmed in *B.O.P Selection* module. After receiving the information for each viewpoints, a distance parameter will be added to the composition evaluation function because the B.O.P is supposed to be in a reachable neighbour of robot's position at present. The viewpoint with the highest scores will be selected as the B.O.P in this module and its position information will send to the next module.

After the B.O.P is determined, a continuous path for the robot will be designed in *Path Planning* module and the moving control is undergoing in *Robot Motion Control* module. Velocity and orientation will be send to the robot from PC in a real time until the robot arrives at the B.O.P.

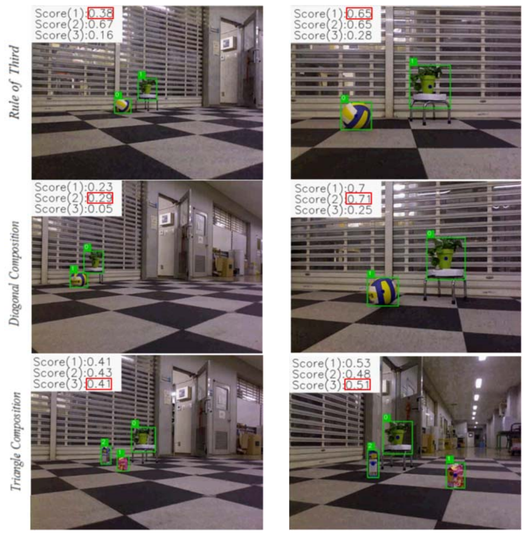
VI. Experiment

A. Experimental Environment

Figure 8 shows the experimental environment. The Monitoring Robot is a omni-directional mobile robot which can move in all kinds of directions with a PC and a RGB-D camera(Xtion Pro Live) fixed on it. Motors of the robot are controlled by a Arduino microcomputer. Our program is divided into two parts: We first upload the moving control part to the microcomputer in advance and image processing and composition evaluating procedure are done in the PC side during the B.O.P searching process. PC and the monitoring robot have a two-way alternating communication in real time by a usb code.

B. Experimental Process

In our experiment, we first appoint a starting point for the robot randomly. We design a user interface from which users can choose some objects as targets and a certain composition rule arbitrarily according to their personal preferences. After



(a) (b)

Fig. 9: Compositions of Initial and Optimal Scenes. (a) Initial Composition. (b) Optimal Composition.

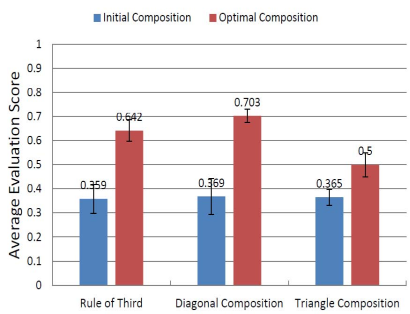


Fig. 10: Evaluation Scores of Initial and Optimal Compositions.

targets and composition rules being input, the robot will confirm the B.O.P and estimate the actual coordinate of it. With a path planning processing in real time, the monitoring robot will approach and then stop at the B.O.P. We repeat this experiment for 10 times based on one certain composition rule and record evaluation scores of initial and optimal compositions.

C. Experimental Result

Figure 9 is scenes taken from a RGB-D camera. Pictures in the left show composition of initial positions and those in the right are from a optimal position. Pictures above are judged by Rule of Third, the two in the middle are based on Diagonal Composition while those below are based on Triangle Composition. Figure 10 shows average scores of the evaluation functions for initial and optimal compositions of scenes. From the result we can see that comparing with initial composition, evaluation scores of the B.O.P selected by our algorithm have an improvement on composition values about 78 percent when using Rule of Third, 90 percent when using Diagonal Composition and 37 percent when using Triangle Composition.

VII. Conclusion

In this paper, we proposed an observation position searching method, which was able to find viewpoints of targets with high aesthetic values instead of image enhancement in a after-processing procedure. Our method could decrease the uneased or uncomfortable feelings of humans when the arrangement of targets was forced to change their semantic characteristics using some methods of previous researches.

We used some well-known compositions (Rule of Third, Diagonal Composition and Triangle Composition) in the field of photography and let a monitoring robot act as a photographer to seek the best observation position with high aesthetic values. We proposed a composition evaluation function for each kind of compositions, which was verified to have a high consistency to human evaluation, with two common parameters and one feature parameter of a photo. We set some alternate observation points around the targets and gave scores to scenes of all the points. The best observation position, where we can get a optimal composition of targets, was marked in a composition map which was drawn to show the relative position relationships between the best observation position and the position where the monitoring robot was at present. We also developed an algorithm for robot's moving with a path planning and a feedback process.

We demonstrated that different composition rules in art field can be computationally evaluated by our system. As the result showed in Section 5, comparing with initial compositions, evaluation scores of the B.O.P selected by our system have an improvement on composition values about 78 percent when using Rule of Third, 90 percent when using Diagonal Composition and 37 percent when using Triangle Composition.

In this paper, we dealt with only the relative position of the objects and do not take the background of photographs into consideration as a component of composition. Since the background parameters sometimes change aesthetic values, some background evaluation parameters will be introduced in order to extend the evaluation function in our future work.

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